Power Variable Training STAP

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Abstract For GMTI radar processing, space-time adaptive processing (STAP) is a standard technique to mitigate clutter while preserving moving targets. STAP relies on an accurately estimated covariance matrix, which is traditionally computed from localized training around the range gate under test. This presentation suggests a new approach to covariance training. Power variable training combines phase-selective covariance training, which restricts range gate training to the most powerful range gates that lie on the clutter ridge, and a new technique that scales the covariance matrix power to prevent over-nulling. The new algorithm exhibits improved minimum detectable velocity (MDV) and fewer false alarms from clutter discretes as well as increased performance with extended-range targets. The proposed technique is demonstrated and compared to localized training on Tuxedo data.

Report Documentation Page	*Form Approved* *OMB No. 0704-0188*

1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED
20 DEC 2004	**N/A**	**-**

4. TITLE AND SUBTITLE	
Power Variable Training STAP	5a. CONTRACT NUMBER
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **MIT Lincoln Laboratory 244 Wood Street Lexington, MA 02420-9108**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR'S ACRONYM(S)
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release, distribution unlimited

13. SUPPLEMENTARY NOTES
See also, ADM001741 Proceedings of the Twelfth Annual Adaptive Sensor Array Processing Workshop, 16-18 March 2004 (ASAP-12, Volume 1)., The original document contains color images.

14. ABSTRACT

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			
unclassified	**unclassified**	**unclassified**	**UU**	**30**	

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March 16, 2004

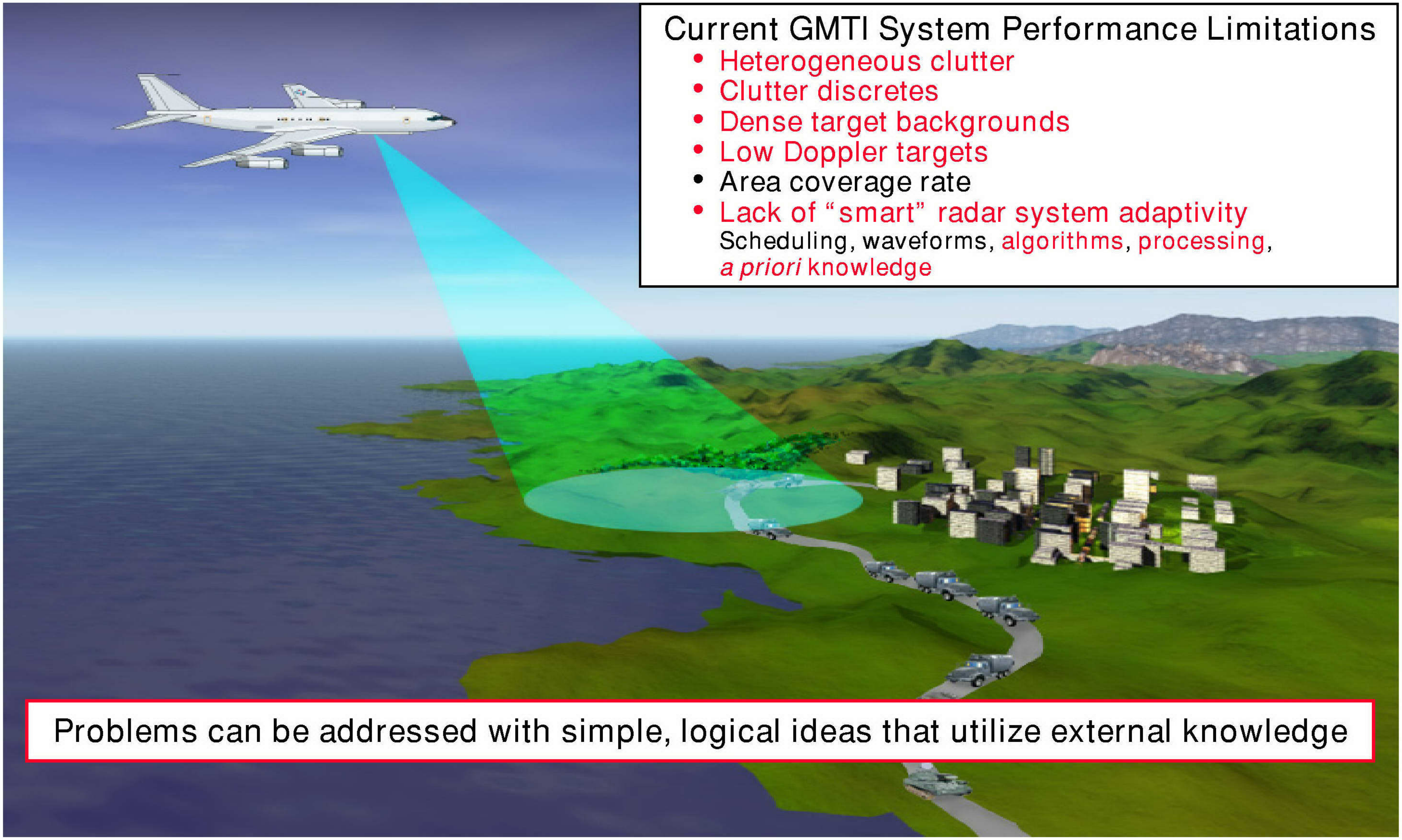
This work is sponsored by the Defense Advanced Research Projects Agency (DARPA), under Air Force contract F19628-00-C-0002. Opinions, interpretations, conclusions and recommendations are those of the authors, and are not necessarily endorsed by the United States Government.

Acknowledgements

Work developed for KASSPER program
Sponsored by DARPA SPO

Lydia Chen
Steve Kogon
Amy Lehan
Bipin Mathew
Paul Monticciolo
Dan Rabinkin
Glenn Schrader
Ali Yegulalp

Current GMTI Issues



Current GMTI System Performance Limitations

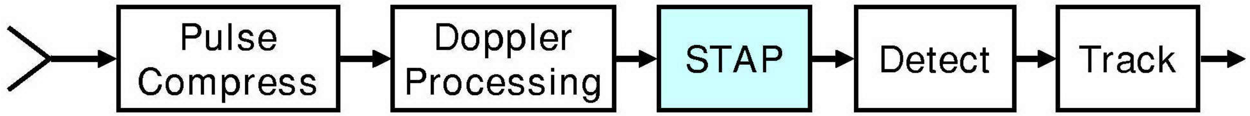
- Heterogeneous clutter
- Clutter discretes
- Dense target backgrounds
- Low Doppler targets
- Area coverage rate
- Lack of "smart" radar system adaptivity
  Scheduling, waveforms, algorithms, processing, *a priori* knowledge

Problems can be addressed with simple, logical ideas that utilize external knowledge

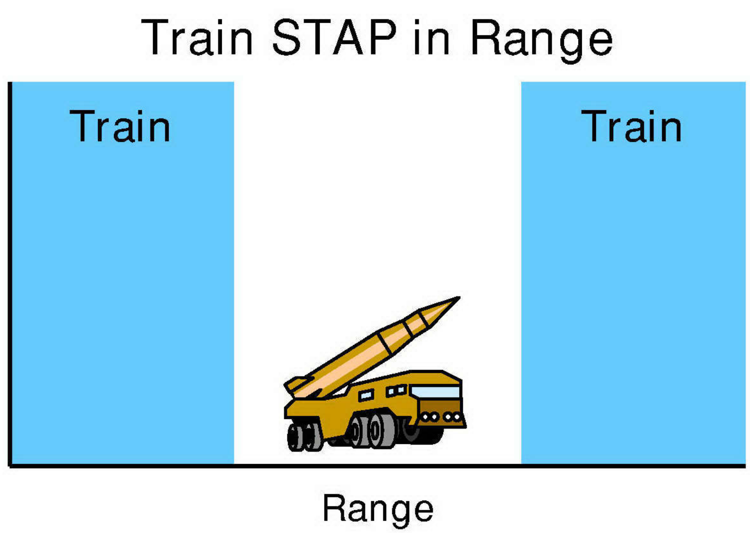
Outline

- Current STAP challenges
- Power variable training with excision algorithm
- Detection and angle estimation
- Tuxedo data results
- Conclusions

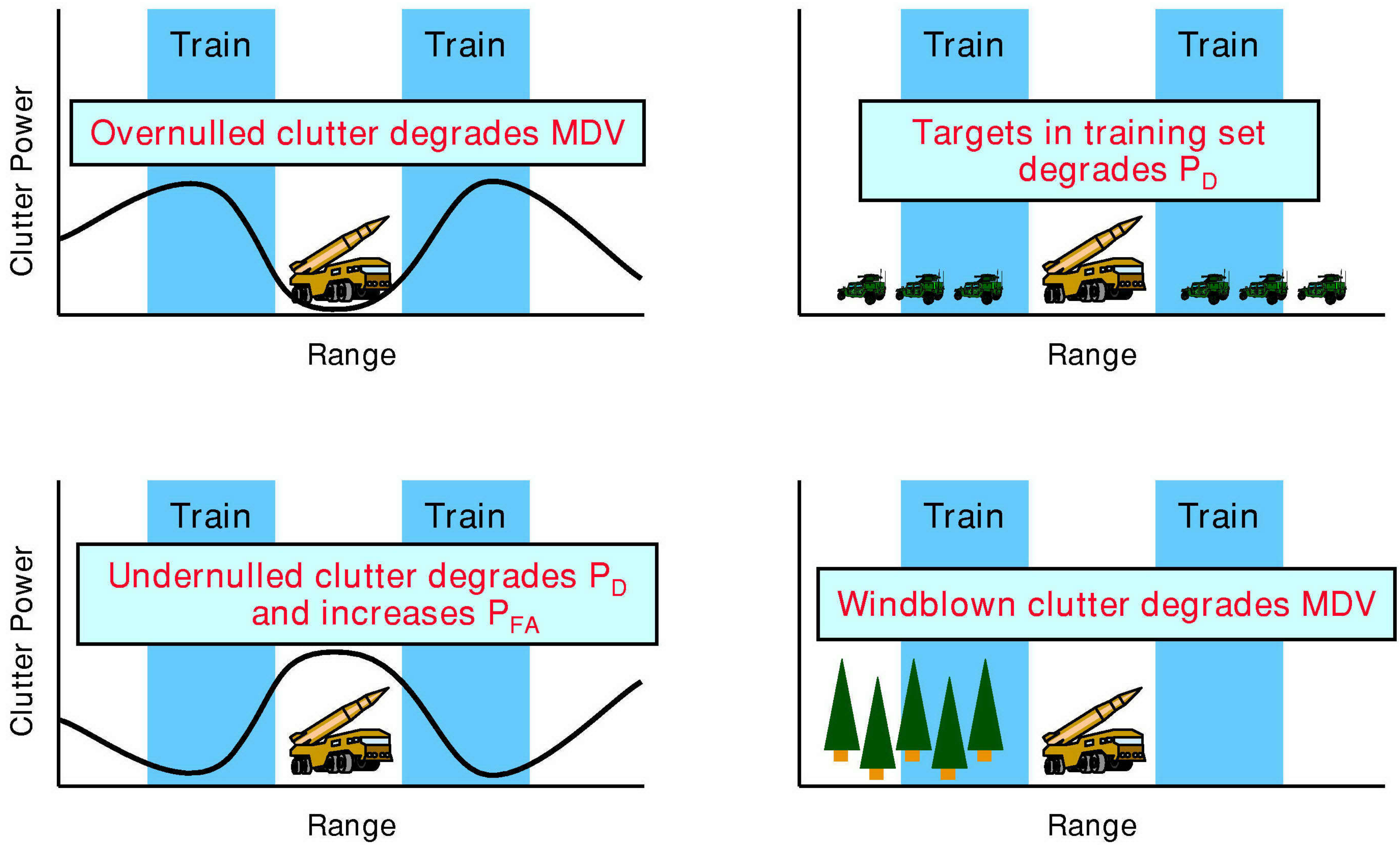
Desirable Features for STAP Training



- Training statistics must match the cell under test
  - Angle/Doppler relationship
  - Clutter type (vegetation / mountain / desert)
  - Power
- The training set should ***NOT*** include targets or other moving objects



Localized Training Impact

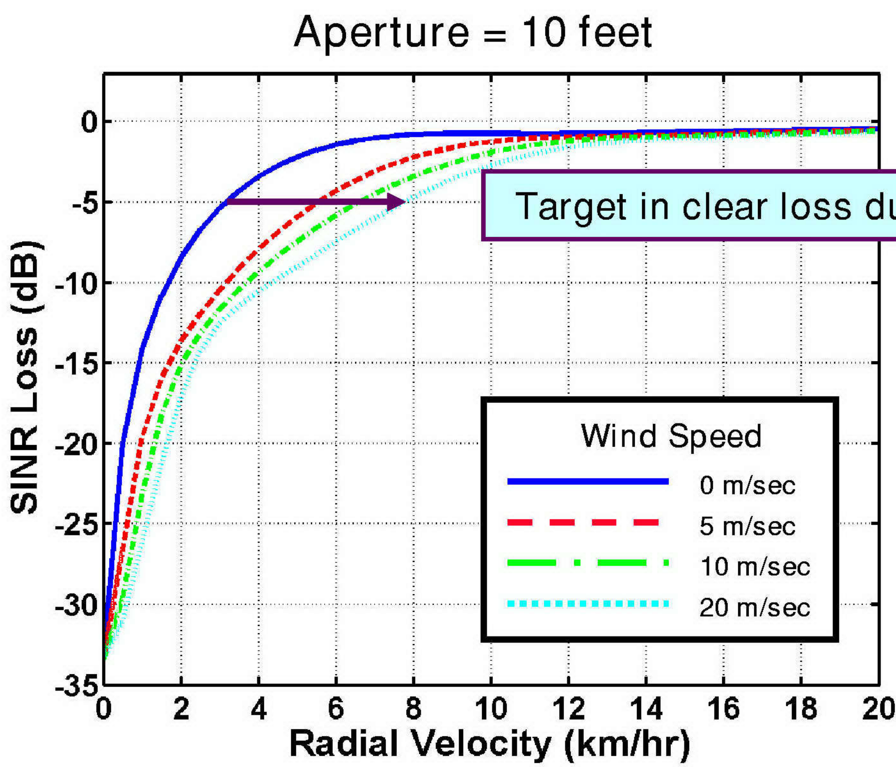


SINR Loss in 50% Wind-Blown Clutter

Target in the clear (no foliage)
Train with 50% wind blown clutter from foliage

Train

Train



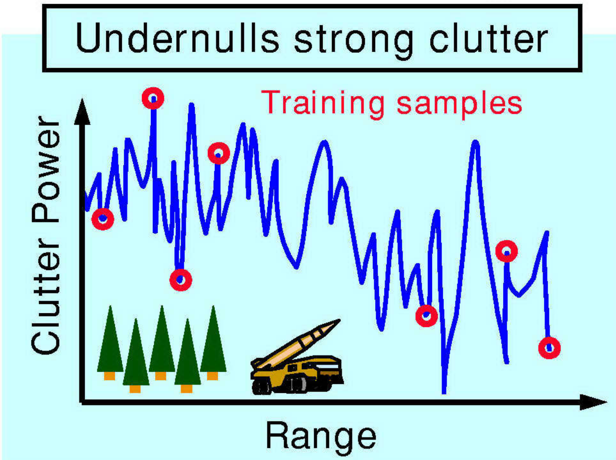
Target in clear loss due to foliage training

Platform velocity = 150 m/sec
Altitude = 10 km
CNR = 35 dB
f0 = 10 GHz
PRF = 2 kHz
50% mixture (wind-blown & stationary)

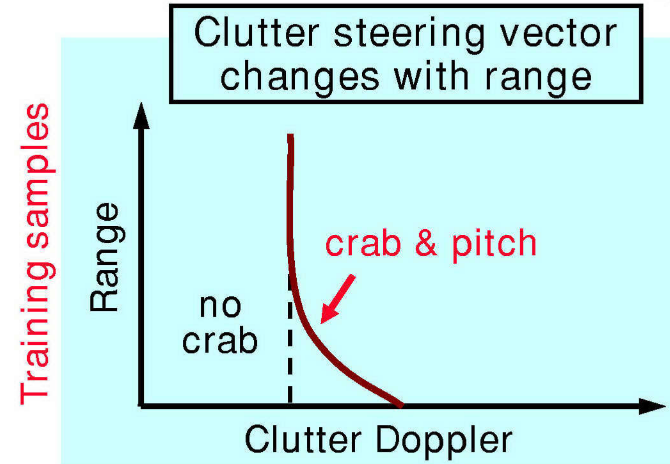
Wind blown foliage training degrades performance in clear

Distributed Training

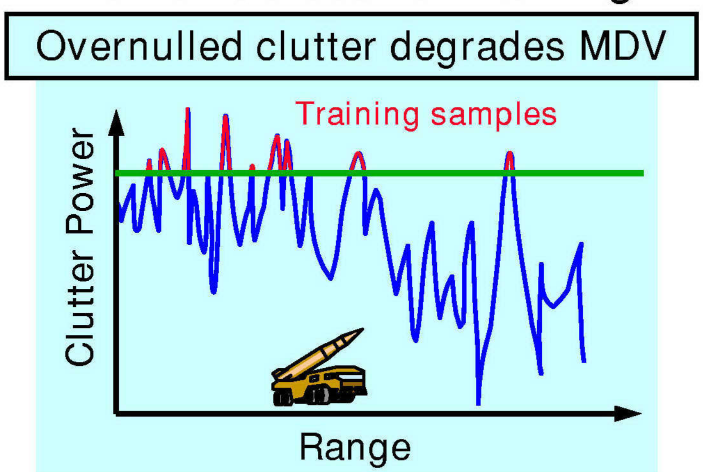
Random Training



Locus of Constant Cone Angle



Power Selective Training



STAP Training Issues:
- Windblown clutter
- Angle/Doppler relationship
- Targets included in training
- Correct power

Neither localized nor distributed training address these issues which affect MDV, P_D, and P_{FA}

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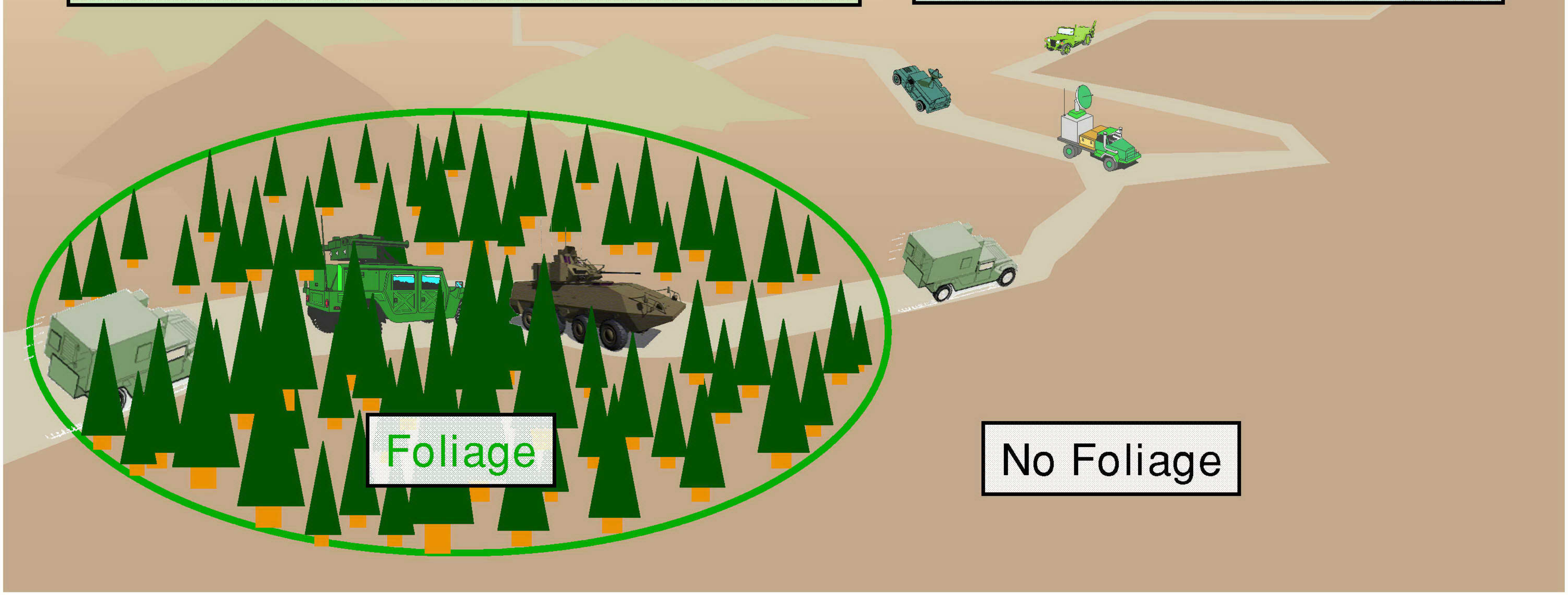
Regionalized Training

TRAINING SAMPLES

- No windblown clutter for targets in clear
- Right angle-Doppler relationship for clutter
- Eliminate targets from training data
- Correct clutter power

- Classify ground swath regions
  - Foliage
  - No foliage
  - Urban
- Apply STAP separately for each region



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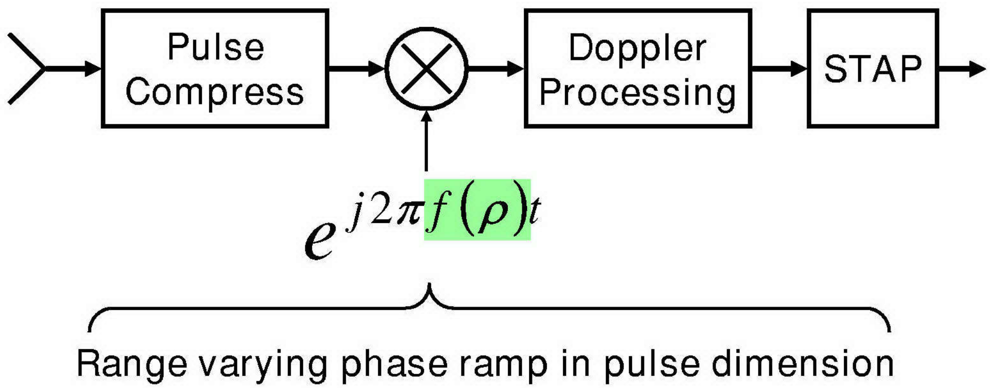
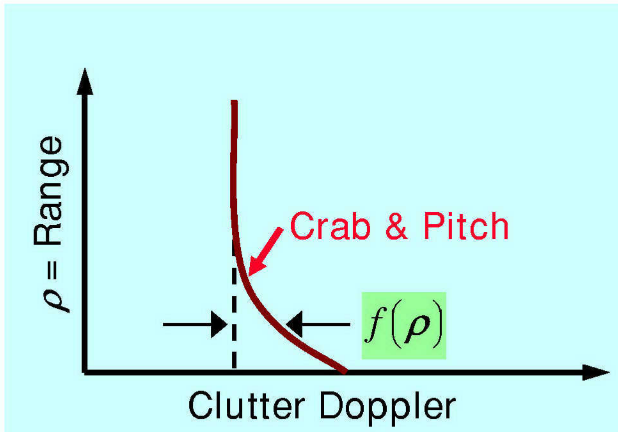
Doppler Warping and Power Selected Training

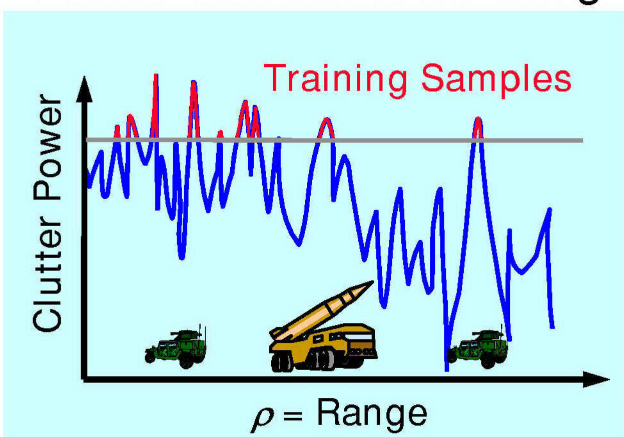
Doppler Warping Aligns Clutter



Locus of Constant Cone Angle



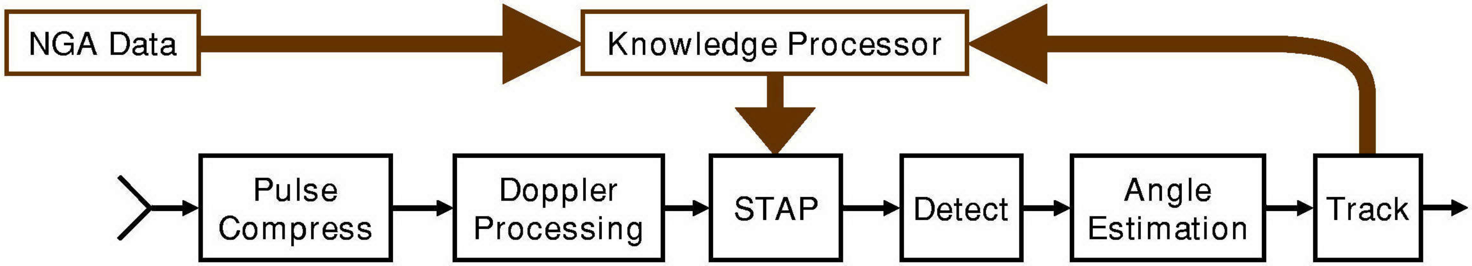
Power Selective Training



TRAINING SAMPLES

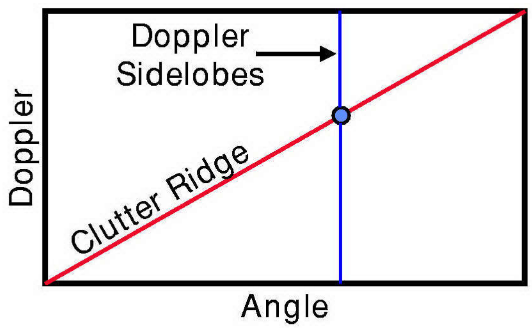
- No windblown clutter for targets in clear
- Right angle-Doppler relationship for clutter
- Eliminate targets from training data
- Correct clutter power

Mapped Discretes and Tracker Feedback



- Don't train or detect on problematic clutter discrete range gates
  - High Doppler sidelobes
- Clutter discretes may be provided by tracker or external NGA map data

- Tracker predicts where targets will exist in future CPIs
- This knowledge is utilized to prevent known targets from being included in STAP training data

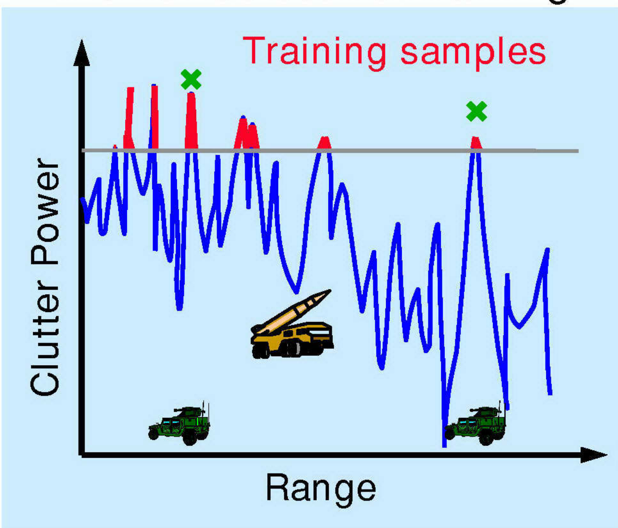


TRAINING SAMPLES

- No windblown clutter for targets in clear
- Right angle-Doppler relationship for clutter
- Eliminate targets from training data
- Correct clutter power

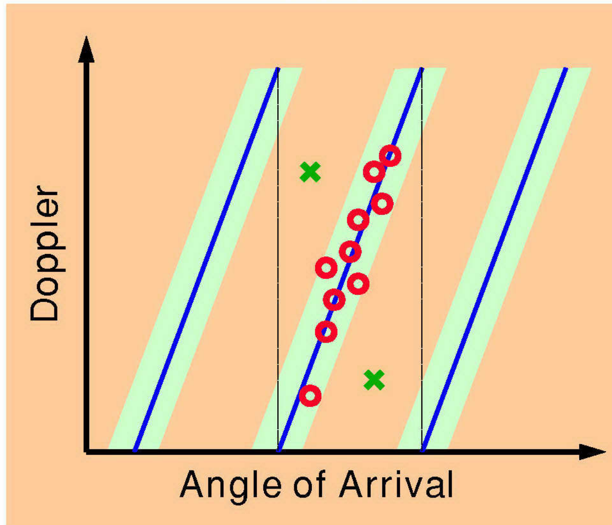
Target Excision

Power Selective Training



Select strongest clutter returns as candidate training samples

Excision



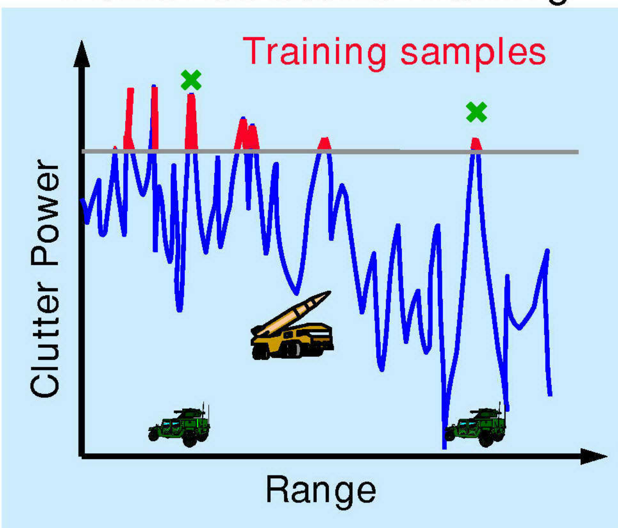
Excise samples away from clutter ridge (potential targets)

TRAINING SAMPLES

- No windblown clutter for targets in clear
- Right angle-Doppler relationship for clutter
- Eliminate targets from training data
- Correct clutter power

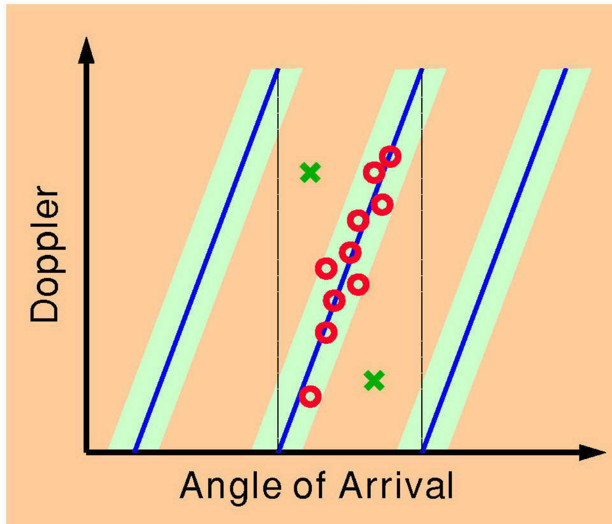
Power Variable Training with Target Excision

Power Selective Training



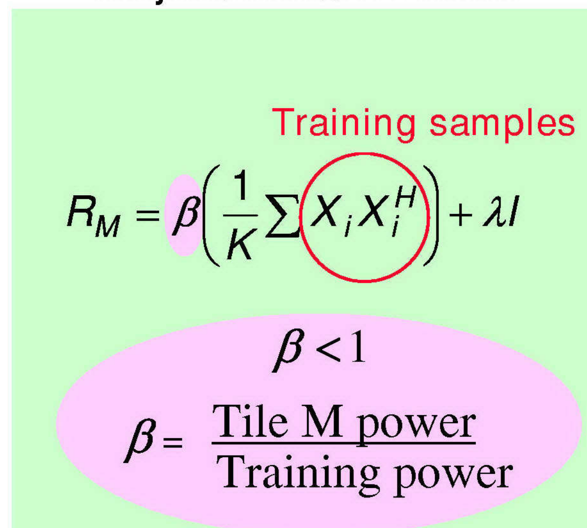
Select strongest clutter returns as candidate training samples

Excision



Excise samples away from clutter ridge (potential targets)

Adjust Clutter Power



$$R_M = \beta\left(\frac{1}{K}\sum X_i X_i^H\right) + \lambda I$$

$$\beta < 1$$

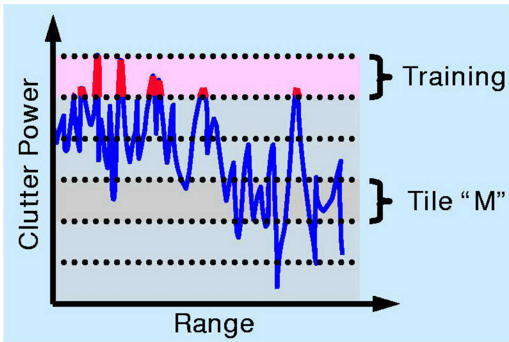
$$\beta = \frac{\text{Tile M power}}{\text{Training power}}$$

Scale training samples to estimated CNR for Tile

TRAINING SAMPLES

- No windblown clutter for targets in clear
- Right angle-Doppler relationship for clutter
- Eliminate targets from training data
- Correct clutter power

Power Variable Training for STAP



Covariance Matrix: $R_S = \frac{1}{K_S} \sum x_i x_i^H$

Tile Power: $e_M = \frac{1}{K_M} \sum x_i^H x_i$

Estimate Pure Clutter Covariance Matrix	$R_C = R_S - \lambda I$	$\lambda =$ Estimated Noise Floor
Covariance Matrix for Tile "M"	$R_M = \beta R_C + \lambda I$	$\beta = \frac{e_M - N\lambda}{tr[R_S] - N\lambda}$
Diagonally Loaded Covariance for Tile "M"	$R_M = \beta R_C + (\lambda + \delta) I$	$\delta =$ Diagonal Load Level
Adaptive Weight for Tile "M" with AMF Normalization	$w_M = \frac{R_M^{-1} v}{\sqrt{v^H R_M^{-1} v}}$	

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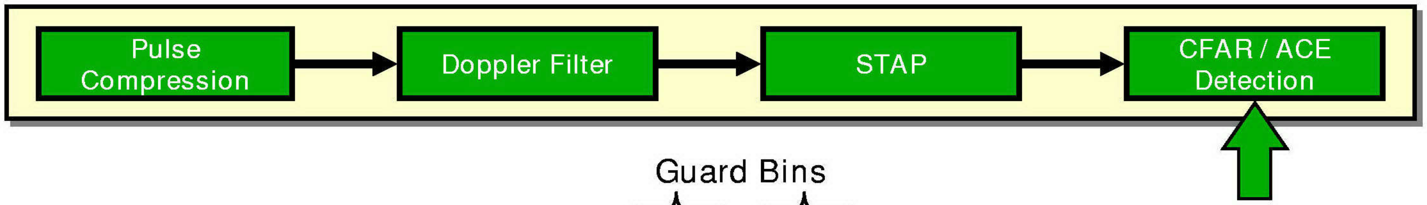
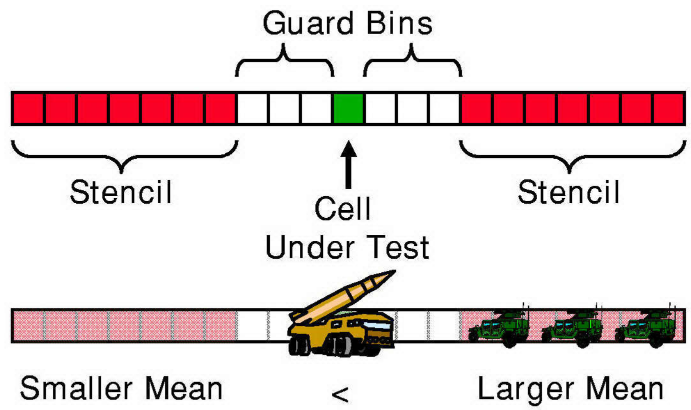
Lesser-Of CFAR Target Detection with ACE





On each side of cell under test:
50 range bin stencil
10 range bin guard
13 dB threshold
0.35 ACE threshold

$$\frac{\left|w^H x_i\right|^2}{x_i^H R_M^{-1} x_i} \overset{?}{>} \chi_{ACE}$$

- Choose *lesser of* training window means for noise estimate
  - Stencil with lesser mean will be least likely to include targets
- Two pass architecture
  - First pass identifies targets
  - On second pass, exclude first-pass targets from stencils
- Small ACE values implies target is better suited by another beam or is associated with sidelobes
- Targets must satisfy CFAR threshold *and* ACE threshold for detection

Knowledge Aided Detection Management

- Estimate arrival angle for each detection:

Spatial Steering Vector:

$$a(\theta) = \begin{bmatrix} 1 \\ e^{j\theta} \\ \vdots \\ e^{j(N-1)\theta} \end{bmatrix}$$

Apply linear transformations to match STAP output:

$$h(\theta) = W\left(Fb \otimes a(\theta)\right)$$

Doppler steering vector
Doppler processing transformation
STAP weight transformation

Find angle that maximizes inner-product:

$$\angle = \arg\max_{\theta} \left| h(\theta)^H x_{STAP} \right|$$

- Delete or flag detections with angle estimates that closely match clutter ridge location
- Use knowledge of road locations to discriminate angle ambiguities

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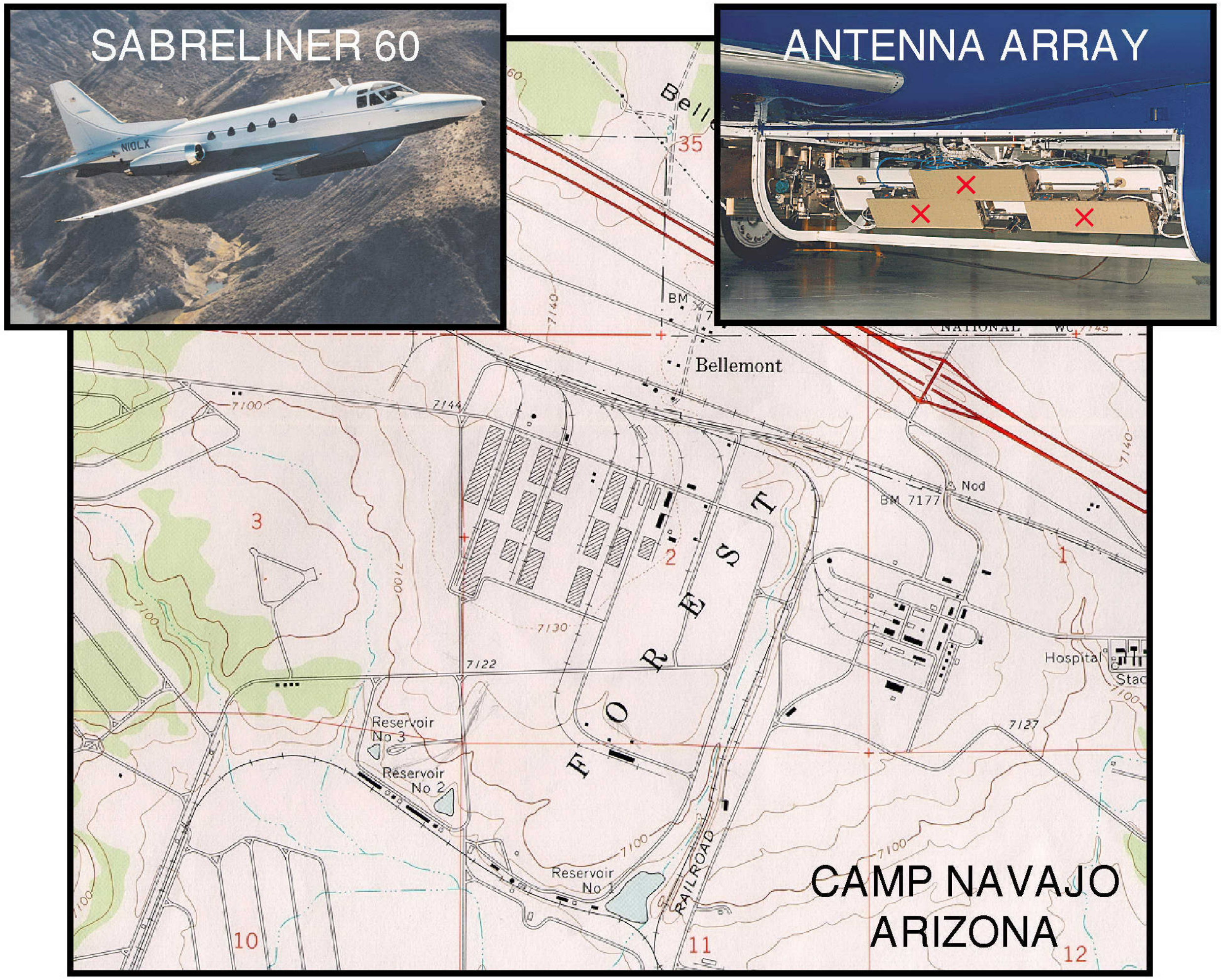
Tuxedo Data

Recorded Data



System Parameters for GMTI Mode

Center Freq.	9.6 GHz
Bandwidth	66 MHz
PRF	1,400 Hz
Tx Apertures	1
Rx Apertures	3
Horiz. Aperture	1.83 m
Vert. Aperture	0.18 m
Az BW	3.6 deg
El BW	9.1 deg
Polarization	HH
A/C Heading	290 deg
Depr. Angle	15 deg
Recorded Time	40-60 sec

Limited targets in data (up to 5) and uniform terrain type (desert)

Demonstrated GMTI Enhancements

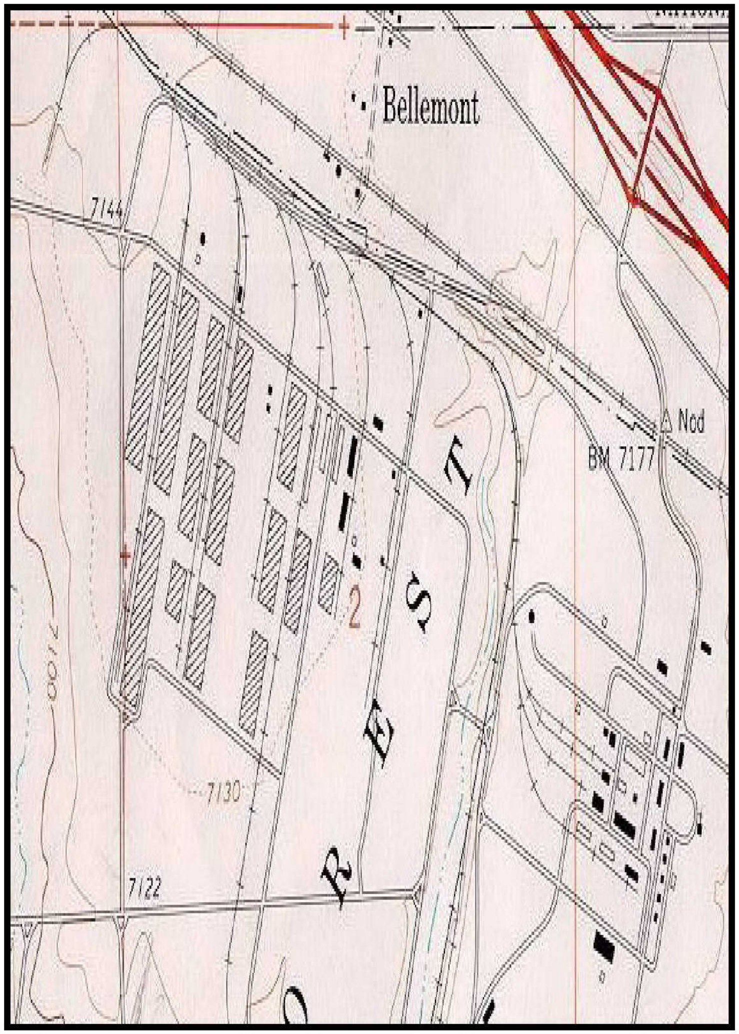
Demonstrated:

- Power Variable Training with Excision
- Tracker feedback of target locations
- Doppler Warping to account for aircraft crab
  - Near broadside collection
- Angle estimation rejection of clutter discretes
- Prior knowledge of problematic clutter discrete locations
- Use of platform inertial data to estimate clutter ridge location
- Use of road locations to discriminate angle ambiguities

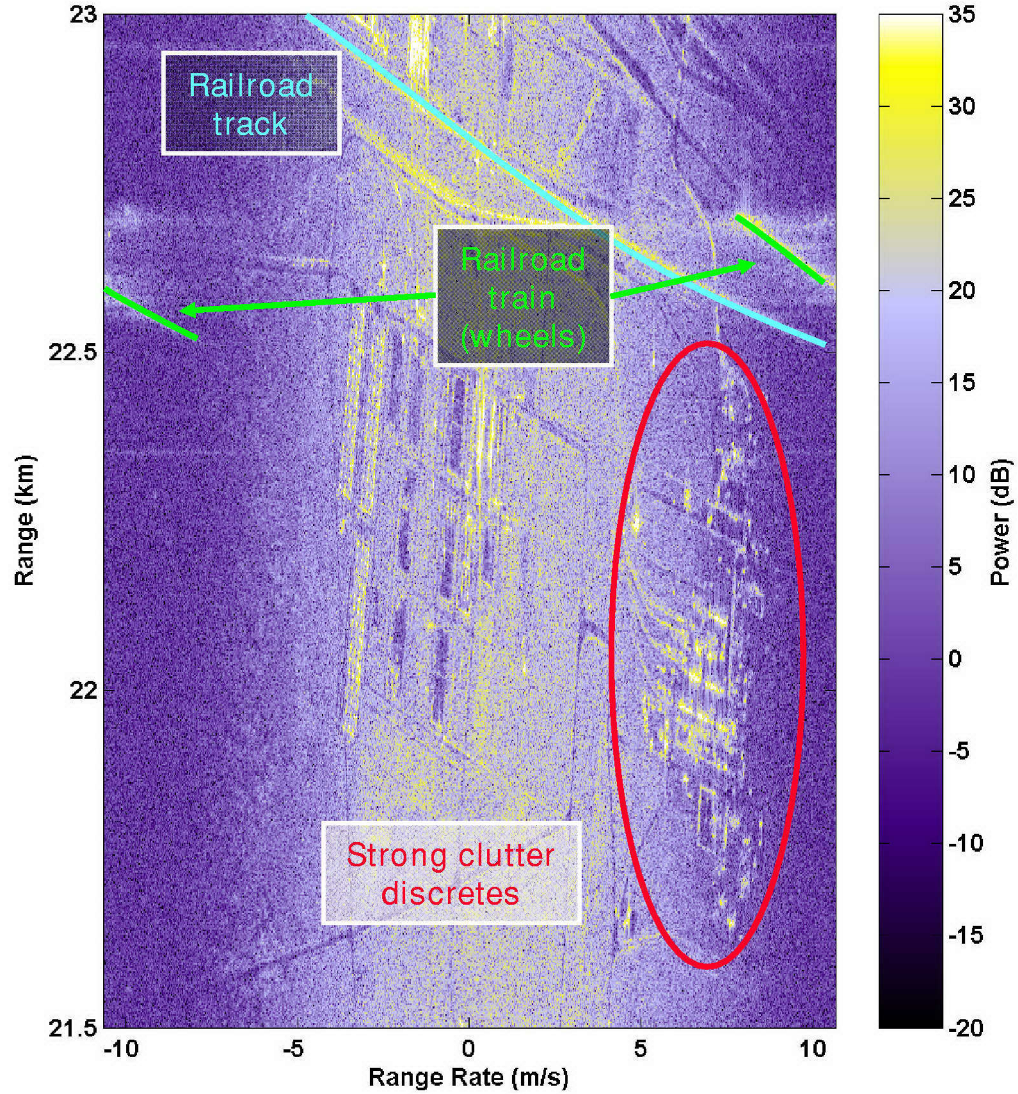
Not Demonstrated:

- Separate training for windblown clutter
  - No significant foliage present in data
- DTED enhanced clutter ridge estimation
  - Flat terrain

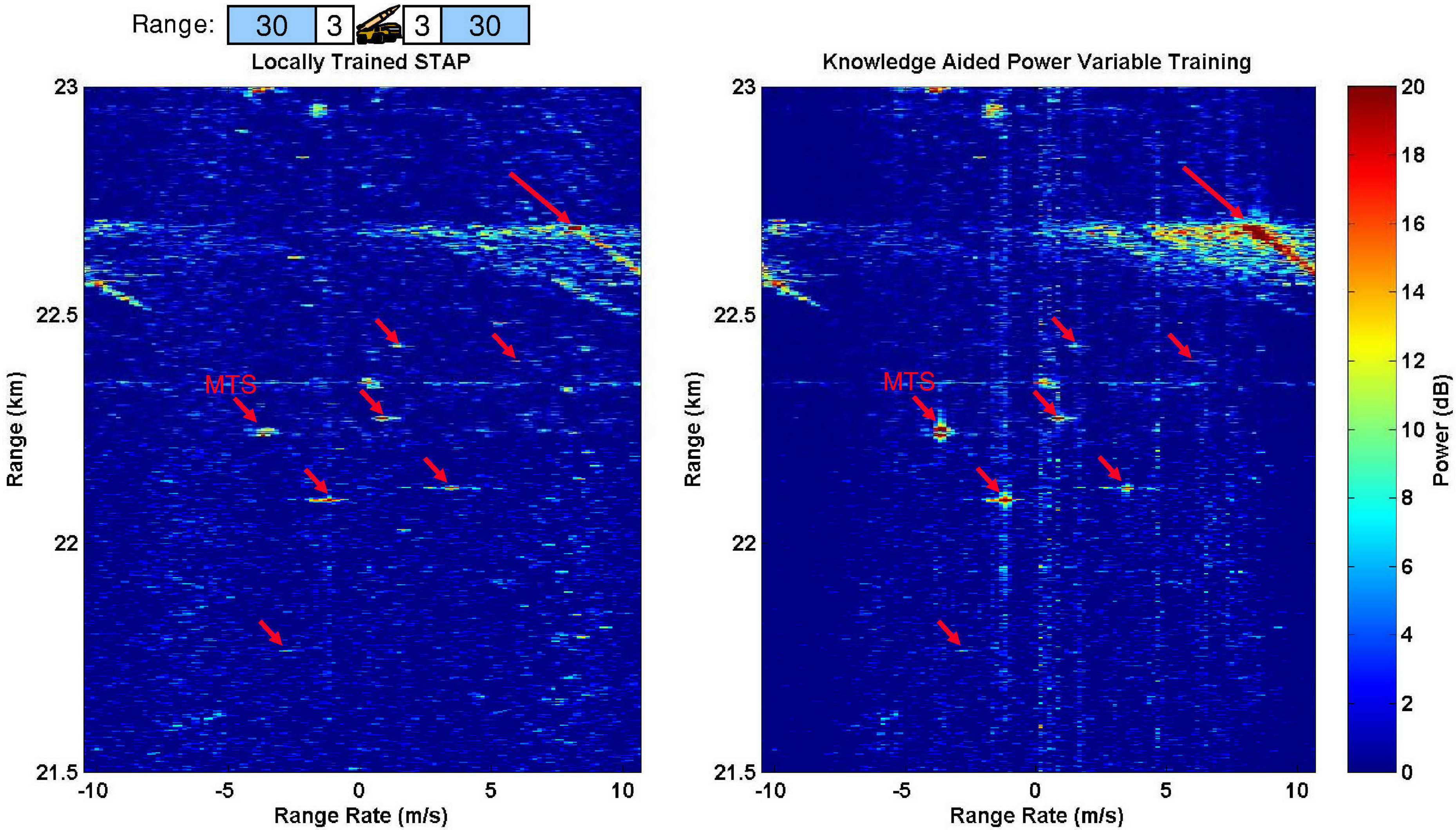
Range-Doppler Image



(map cropped and stretched to match data)

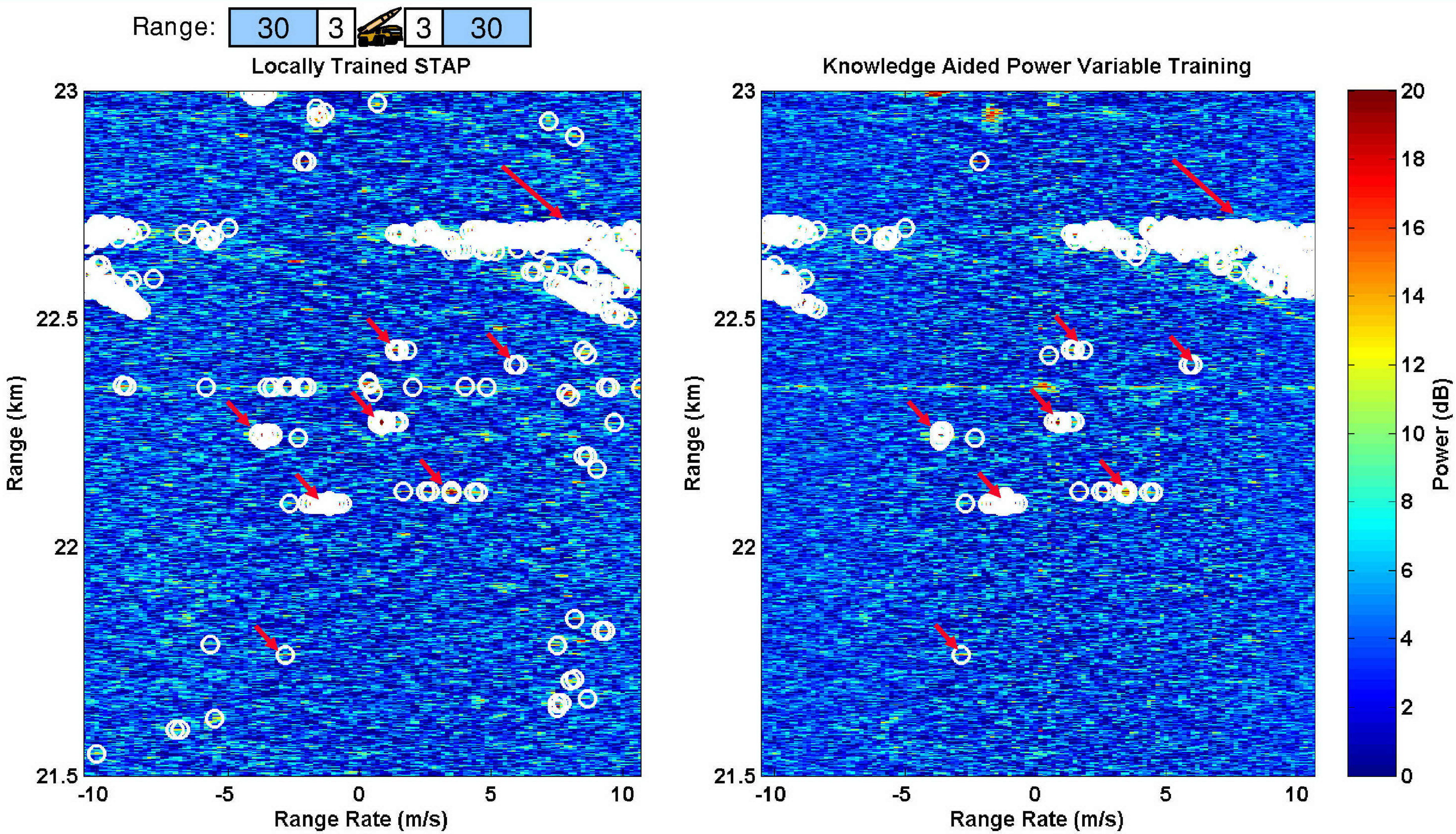


Power Variable Training Comparison: STAP Output



Railroad train self-nulled with localized training

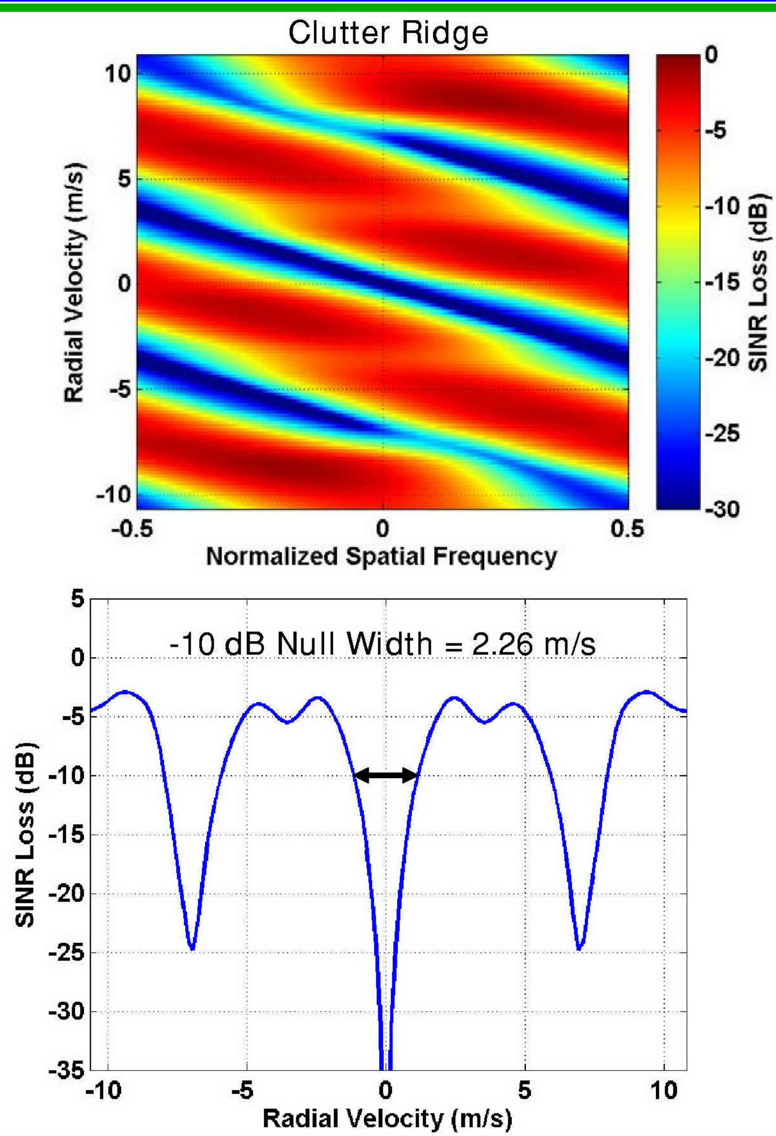
Power Variable Training Comparison: Detector Output



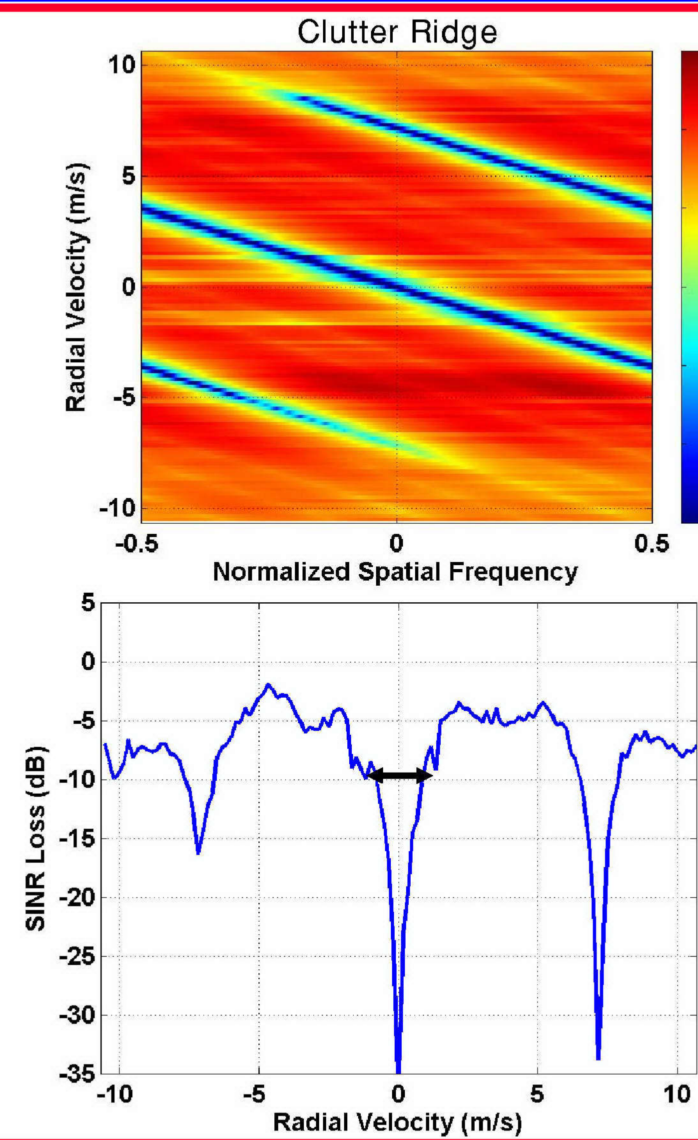
Power variable training dramatically reduces false alarm rate

SINR Loss
Simulation and Data Results

Simulation

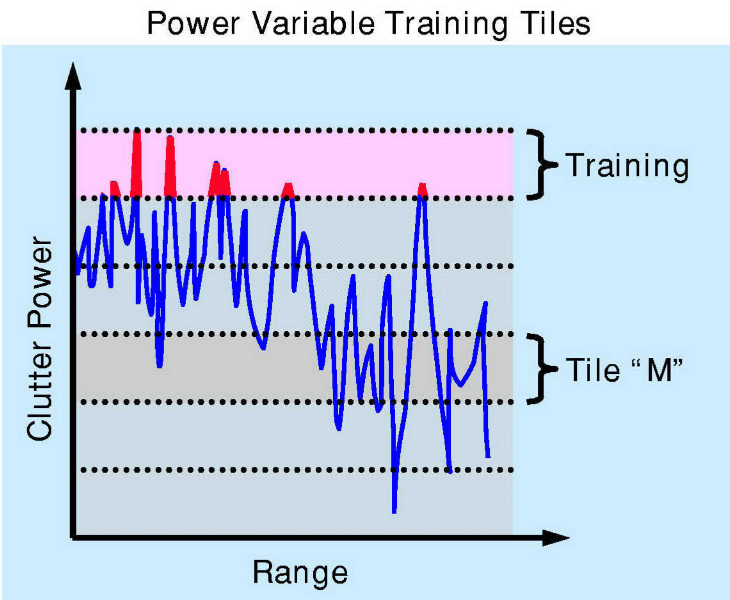


Knowledge Aided Power Variable Training

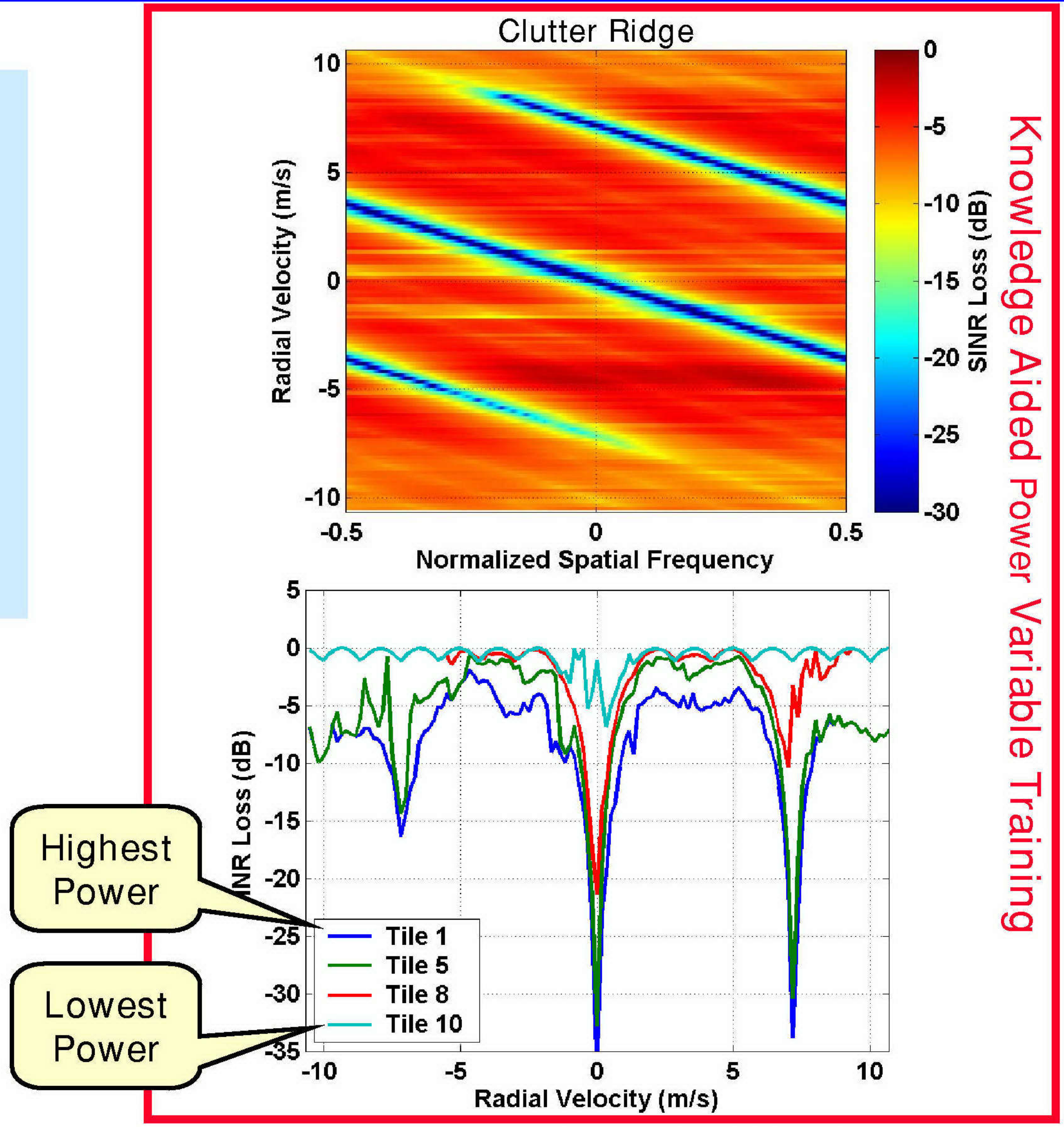


20 dB Taylor element taper

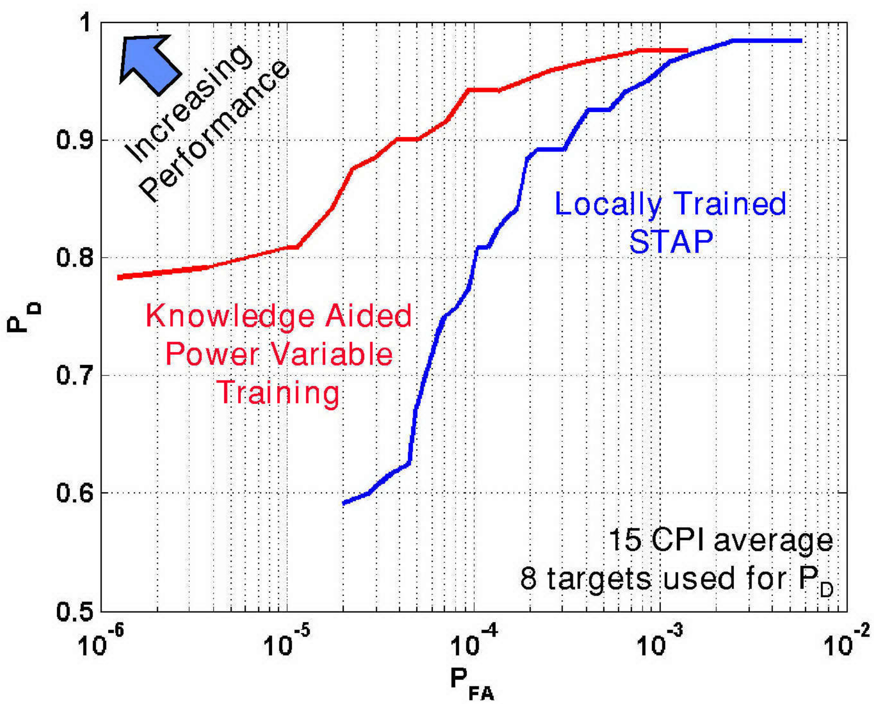
Power Variable SINR Loss Effects

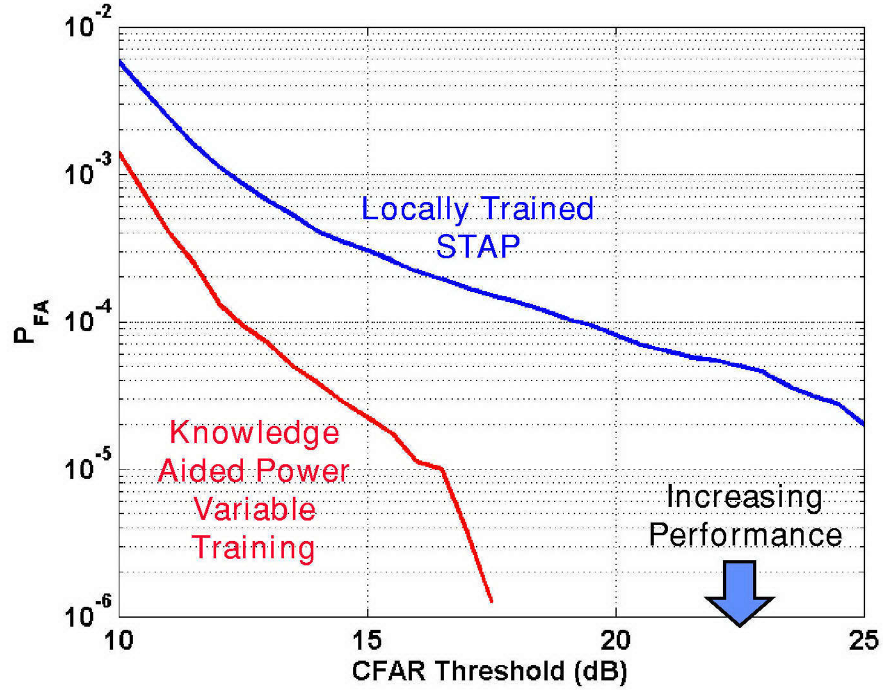


- Tile SINR loss approaches 0 dB as tile power decreases
- Significantly improved MDV for lower power range gates



ROC Comparison

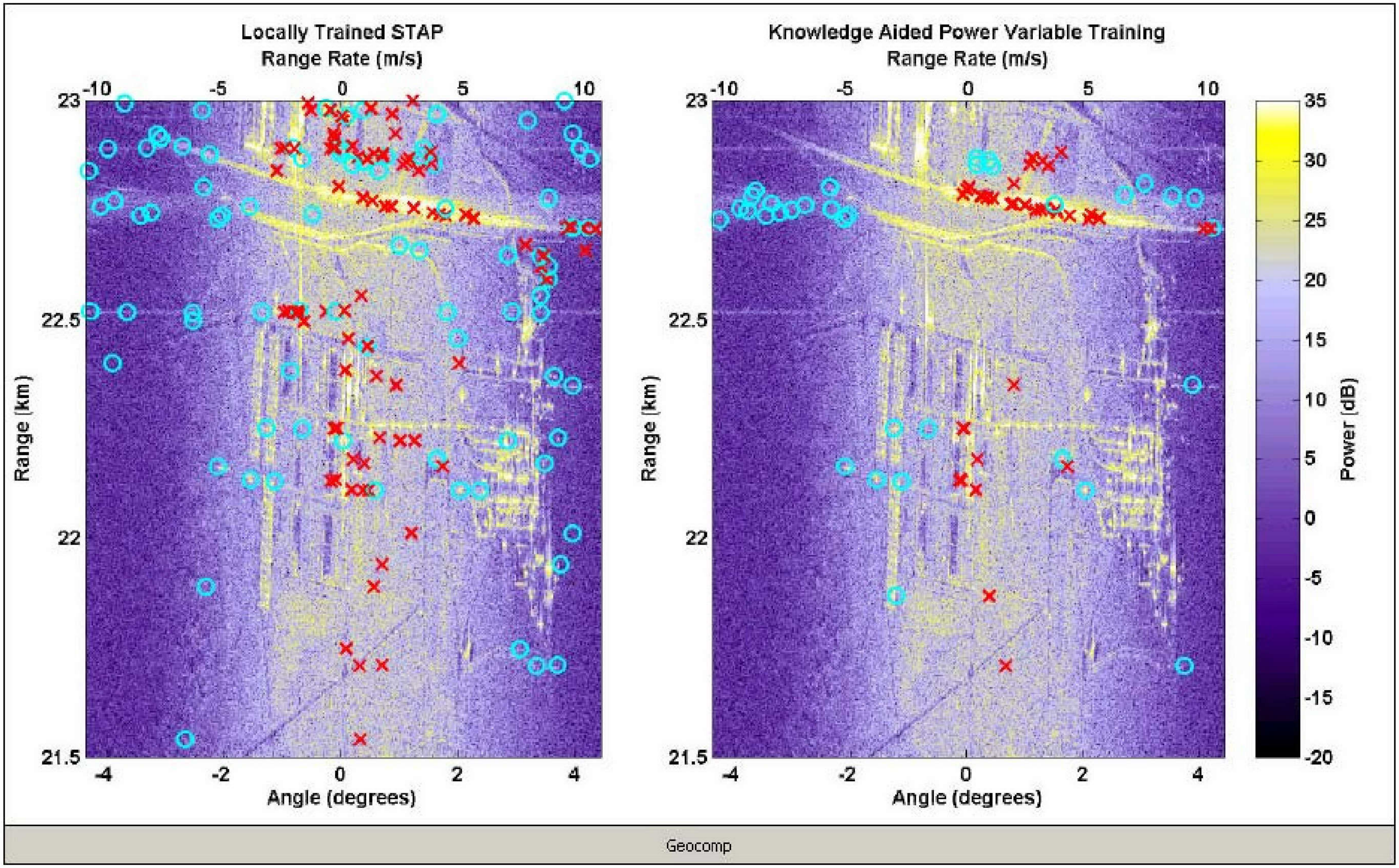




- Overall ROC curve illustrates performance increase
- Significant P_{FA} benefits demonstrated
- Performance gain primarily from P_{FA}

Comparison Movie

Detection
Angle Localization



Conclusions

- Use of internal and external knowledge improves performance
  - Tracker feedback
  - External data maps
- Simple, "smart" enhancements significantly improve overall performance
  - Validated improvements with tuxedo data
- Enhanced algorithm data results
  - Probability of false alarm significantly decreased
  - SINR Loss closely matches predicted performance
  - Targets of interest consistently detected
  - Low MDV observed
  - "Convoy-like" railroad train easily detected and not self-nulled